

Improved Estimation of Weibull Parameters Considering Unreliability Uncertainties

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Abstract—We propose a linear regression method for estimating Weibull parameters from life tests. The method uses stochastic models of the unreliability at each failure instant. As a result, a heteroscedastic regression problem arises that is solved by weighted least squares minimization. The main feature of our method is an innovative s-normalization of the failure data models, to obtain analytic expressions of centers and weights for the regression. The method has been Monte Carlo contrasted with Benard's approximation, and Maximum Likelihood Estimation; and it has the highest global scores for its robustness, and performance.

ACRONYMS

HUWE	Heteroscedastic Unreliability Weibull Estimation.
LR	Linear Regression.
MLE	Maximum Likelihood Estimation.
MRSE	Mean Relative Squared Error.
MSE	Mean Squared Error.
WLS	Weighted Least Squares.

NOTATION

t	The time counted from the beginning of a widget's life
F	Unreliability, failure probability of a widget
η, β	Scale parameter, and shape parameter of a Weibull distribution
N_M	Number of widgets in a life test
T	Number of Monte Carlo trials for evaluation of estimators

I. INTRODUCTION

THE Weibull model is the most popular, widely used model in reliability theory [1]. It states the unreliability as a function of time in the form

$$F(t; \eta, \beta) = 1 - \exp \left[- \left(\frac{t}{\eta} \right)^\beta \right]. \quad (1)$$

The failure profile of a specific type of widgets is described by its η and β values. These parameters are estimated with the help of a *life test*, which is an experiment that outputs the series of failure times $\{t_k\}$ of a set of widgets of the kind that one wishes to analyse. The ranks $k \in [1, N_M]$ are natural labels that maintain a coherent order with respect to the failure times, that is $k_i > k_j \Leftrightarrow t_{k_i} \geq t_{k_j}$.

Bayesian methods [2] are the most rigorous, complete approaches to parameter estimation, but they are difficult to obtain and interpret. Moreover, the prior conjugate joint distribution for the Weibull parameters is not continuous [1], [3], which makes the approach even harder. Perhaps due to this complexity, Maximum Likelihood Estimation (MLE) [4]–[7], and Linear Regression (LR) [8], [9] approaches are commonly used. Although MLE estimators offer better accuracy when N_M is large enough, LR is preferred in some environments for the following reasons.

- The MLE shape parameter estimator $\hat{\beta}$ is s-biased when the sample size is small [10], [11], although resources [5], [12]–[14] have been developed to overcome this drawback.
- MLE leads to equations that are not solvable in explicit form, so numerical procedures are needed, and convergence and numerical problems arise [15], [16].
- Engineers often choose LR methods because of their computational simplicity, and ease of graphical interpretation [17]–[19].

LR methods proceed transforming the Weibull failure model (1) to obtain an affine model suitable to be fitted by regression techniques. Isolating the exponential in the second term of (1), and taking logarithms leads to a first reliability-related variable

$$\Phi = \ln \left(\frac{1}{1 - F} \right) = -\ln(1 - F) = \left(\frac{t}{\eta} \right)^\beta. \quad (2)$$

Taking logarithms once again leads to a second reliability-related variable

$$Y = \ln \Phi = -\beta \ln \eta + \beta \ln t. \quad (3)$$

From (3), an affine relationship (4) can be established between Y and the time-related variable $X = \ln t$.

$$Y = \beta X - \beta \ln \eta \quad (4)$$

A key problem that arises when regressing on model (4) is how to determine data point coordinates in the (X, Y) space from the life test. Variable X_k can be determined from failure times t_k , and Y_k can be determined from the unreliabilities at failures F_k as in

$$\begin{aligned} Y_k &= \ln(\Phi_k) = \ln\left(\ln\left(\frac{1}{1 - F_k}\right)\right) = \ln(-\ln(1 - F_k)) \\ X_k &= \ln(t_k) \end{aligned} \quad (5)$$

But F_k are probabilities, so they cannot be directly observed. The most straightforward choice for F_k are relative frequencies $F_k = k/N_M$; however, this approach is not very accurate, and gets a strong s -bias under transformations (2) and (3). Indeed, for the last point, $k = N_M$, it yields $F_{N_M} = 1$, which overflows $Y_{N_M} = \ln(-\ln(0)) = \infty$.

A better choice for F_k is Median Rank [11], [20]. Median Rank cannot be put into explicit form, so its value has to be determined by numerical techniques or approximated methods. A simple analytic approach to Median Rank, which has become a standard way to estimate F_k , is Benard's approximation [21]:

$$F_k = \frac{k - 0,3}{N_M + 0,4}. \quad (6)$$

Sometimes it is assumed that Y_k are homoscedastic, i.e. that the Y_k uncertainties are the same for any k ; then the regression line should minimize the simple residual

$$residual(Y) = \sum_{k=1}^{N_M} (Y_k - \hat{Y}_k)^2 = \sum_{k=1}^{N_M} (Y_k - \beta X_k - \beta \ln \eta)^2. \quad (7)$$

In fact, Y_k are heteroscedastic as its uncertainties are not the same. More elaborate regression algorithms such as Weighted Least Squares (WLS) [22], [23] take into account the heteroscedasticity by weighting terms of the residual with uncertainty-related factors w_k (8).

$$weighted\ residual(Y) = \sum_{k=1}^{N_M} w_k (Y_k - \hat{Y}_k)^2 \quad (8)$$

The weights are commonly chosen as the inverses of the variances of Y_k (9).

$$w_k = \frac{1}{\sigma_{Y_k}^2} \quad (9)$$

Uncertainties of Y_k have been considered by some authors. Bergman [24] assumes that the variance $\sigma_{F_k}^2$ of F_k is constant in order to find analytically $\sigma_{Y_k}^2$ in consonance with transformations (2), and (3). Bergman's hypothesis, although it is useful, is not very accurate, as will be shown in Fig. 2, where $\sigma_{F_k}^2$ is plotted against k , revealing a considerable variation. Faucher

and Tyson [25] evaluate F_k uncertainty from the binomial model with prefixed confidence levels. Their method requires carrying numerical tables to evaluate the weights.

In Section II, we develop the Heteroscedastic Unreliability Weibull Estimation (HUWE). HUWE is a new LR method based on the assumption of the s -normality of Y_k . This approximation allows us to find, working exclusively with analytical procedures, highly accurate estimates for Y_k centers and weights in terms of hyper-geometric functions [26]. Analyticity makes HUWE based software straightforward, reliable, and easily portable because it can be designed without numerical tables nor 'ad hoc' iterative solving procedures. It is well known that these two resources compromise the reliability and portability of software: numerical tables because errors while typing can lead to very difficult to detect errors; and 'ad hoc' iterative solving procedures because they involve convergence problems.

To clarify the methodology, an illustrative example of HUWE, applied to a small life test, is given in Section III. In Section IV, a Monte Carlo evaluation procedure is designed to compare HUWE performance with other methods. The results of contrast with Benard and MLE methods are given in Section V. According with these results, HUWE performs the best when we consider a wide range of possible N_M values. Moreover, HUWE is more computationally efficient and robust than MLE, especially when N_M is large, and the shape parameter β is far from 1.

II. HUWE REGRESSION METHODOLOGY

HUWE is a weighted LR method based on a statistical model for F_k that uses as the centralization, and dispersion of Y_k in (8) the means μ_{Y_k} , and variances $\sigma_{Y_k}^2$ respectively.

The problem with this approach is that the exact determination of the moments of Y_k leads to integrals that cannot be put in a closed form.. HUWE fixes this problem by assuming s -normal models for Y_k . This assumption opens up a way to approximate Y_k moments as functions of the moments of the intermediate variables Φ_k . As the moments of Φ_k can be put in closed form, this solves the problem, at the cost of a little information leakage. An outline of the HUWE methodology is depicted in Fig. 1. The steps in Fig. 1 will be described below.

A. Unreliability Data Points F_k Model

A well established [27] statistical model for F_k that assumes the principle of indifference on the prior probability yields

$$\rho_{F_k}(f) = N_M \binom{N_M - 1}{k - 1} f^{k-1} (1 - f)^{N_M - k}. \quad (10)$$

Eqn. (10) gives the probability density function of the unreliability F_k just at the precise instant t_k of the k -th failure of a total of N_M widgets. The model (10) can be derived by considering that the number of ways that N_M failures can consist of $k - 1$ failures before $t_k - (dt/2)$, $N_M - k$ failures after $t_k + (dt/2)$, and just one failure inside $[t_k - (dt/2), t_k + (dt/2)]$, is $N_M! / (k - 1)! (N_M - k)!$.

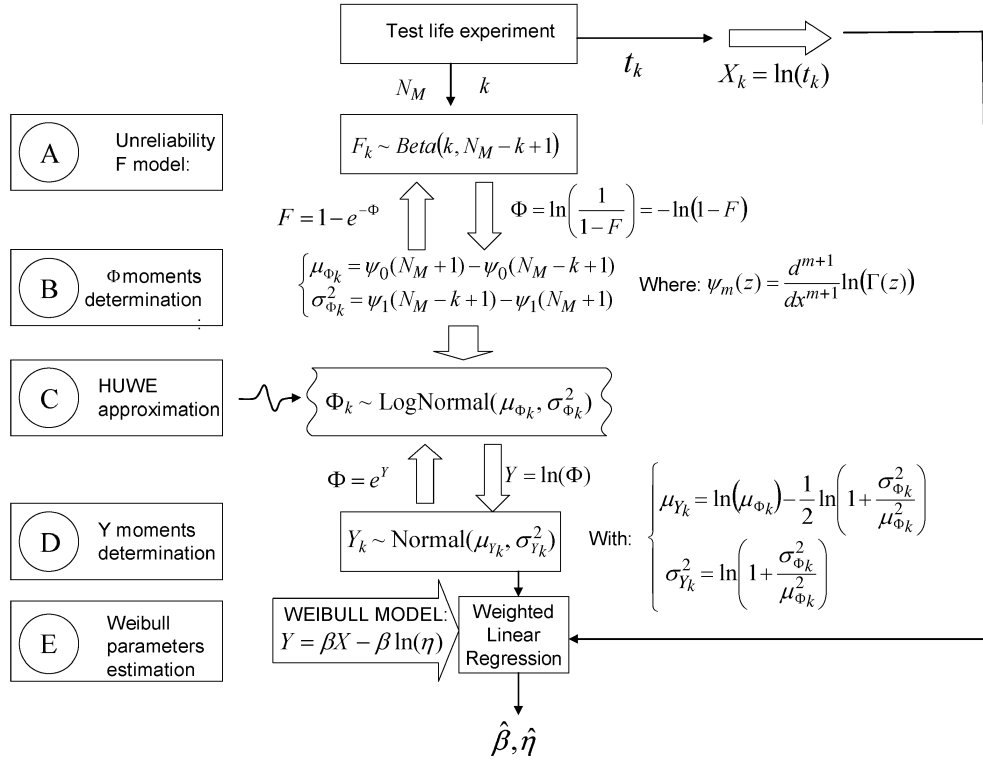


Fig. 1. HUWE methodology explanation.

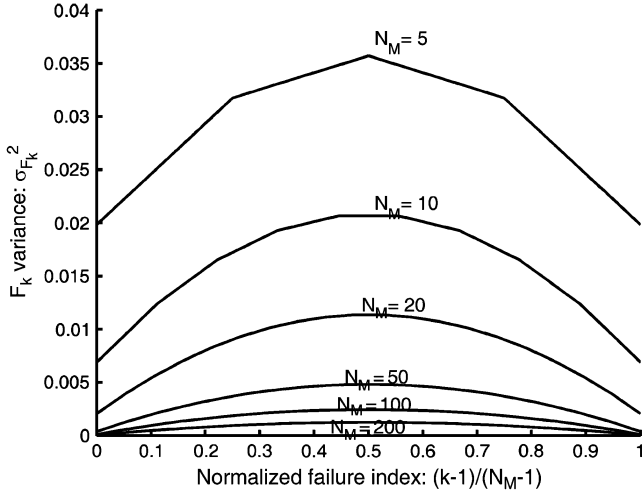


Fig. 2. $\sigma_{F_k}^2$ as a function of the normalized index of failure $k - 1/N_M - 1$ for several values of N_M .

Eqn. (10) can be also expressed in terms of the Beta Euler function, resulting in

$$\rho_{F_k}(f) = \frac{1}{\text{Beta}(k, N_M - k + 1)} f^{k-1} (1-f)^{N_M-k}, \quad (11)$$

or can be summarized in terms of the Beta distribution as

$$F_k \sim \text{Beta}(k, N_M - k + 1). \quad (12)$$

To show the amount of heteroscedasticity of the model (10), in Fig. 2, the variance $\sigma_{F_k}^2$ has been plotted as a function of the normalized rank, $k - 1/N_M - 1$, for several values of N_M .

From Fig. 2, it is clear that $\sigma_{F_k}^2$ is not constant, but reach maxima at about $k - 1/N_M - 1 = 1/2$, and minima for the first, and last failures ($k = 1$, and $k = N_M$). Moreover, it can be established that the ratio between the maximum and minimum variances (that qualifies the degree of heteroscedasticity) grows with N_M as $\sigma_{\max}^2/\sigma_{\min}^2 \approx (N_M + 2)/4$. This result means that Bergman's approximation [24] gets worse as N_M increases.

B. Φ_k Moment Determination

Now we estimate the moments of Φ_k defined as in (13), according to (2).

$$\Phi_k = \ln\left(\frac{1}{1-F_k}\right) = -\ln(1-F_k) \quad (13)$$

By applying the mean and variance definitions to Φ_k , we obtain

$$\begin{aligned} \mu_{\Phi_k} &= \int_0^1 -\ln(1-f) \frac{f^{k-1}(1-f)^{N_M-k}}{\text{Beta}(k, N_M - k + 1)} df \\ \sigma_{\Phi_k}^2 &= \int_0^1 (-\ln(1-f) - \mu_{\Phi_k})^2 \frac{f^{k-1}(1-f)^{N_M-k}}{\text{Beta}(k, N_M - k + 1)} df \end{aligned} \quad (14)$$

1) Mean of Φ_k : For the mean of Φ_k , μ_{Φ_k} , we have

$$\begin{aligned} \mu_{\Phi_k} &= \int_0^1 \phi_k(f) \rho_{F_k}(f) df \\ &= \int_0^1 -\ln(1-f) \frac{f^{k-1}(1-f)^{N_M-k}}{\text{Beta}(k, N_M - k + 1)} df. \end{aligned} \quad (15)$$

Eqn. (15) can be analytically solved given

$$\mu_{\Phi_k} = H_{N_M} - H_{N_M-k} \quad (16)$$

where $H_m = \sum_{j=1}^m (1/j)$ is the m -th harmonic number. Harmonic numbers can be put in terms of the polygamma function [26] $\psi_m(z) = (d^{m+1}/dz^{m+1}) \ln(\Gamma(z))$ as $H_m = \psi_0(m+1) + \gamma = \psi_0(m+1) - \psi_0(1)$, where $\gamma = -\psi_0(1) = 0.57721\dots$ is the famous Euler-Mascheroni constant, and $\Gamma(z) \equiv (z-1)! = \int_0^\infty u^{z-1} e^{-u} du$. Functions $\psi_m(z)$ are implemented in an accurate, robust way in multiple software packets and programs such as EISPACK, MATLAB, and MATHEMATICA.

We can use the former relationships to rewrite (16) in terms of $\psi_m(z)$, and arrive eventually at

$$\mu_{\Phi_k} = \psi_0(N_M + 1) - \psi_0(N_M - k + 1). \quad (17)$$

2) *Variance of Φ_k* : To get $\sigma_{\Phi_k}^2$, we first calculate the non-centered second moment $\mu_{\Phi_k}^2$ of Φ_k to be

$$\begin{aligned} \mu_{\Phi_k}^2 &= \int_0^1 \phi_k^2(f) \rho_{F_k}(f) df \\ &= \int_0^1 (-\ln(1-f))^2 \frac{f^{k-1}(1-f)^{N_M-k}}{\text{Beta}(k, N_M-k+1)} df. \end{aligned} \quad (18)$$

(18) gives $\mu_{\Phi_k}^2 = (H_{N_M} - H_{N_M-k})^2$. Now, by applying the general identity $\sigma_{\Phi_k}^2 = \mu_{\Phi_k}^2 - \mu_{\Phi_k}^2$, taking into account (16), and using polygamma functions, we reach

$$\sigma_{\Phi_k}^2 = \psi_1(N_M - k + 1) - \psi_1(N_M + 1). \quad (19)$$

Collecting the above expressions for the mean (17), and the variance (19), a remarkable symmetry becomes evident that widely justifies the transformations of both expressions in terms of polygamma functions (20):

$$\begin{aligned} \mu_{\Phi_k} &= +\psi_0(N_M + 1) - \psi_0(N_M - k + 1) \\ \sigma_{\Phi_k}^2 &= -\psi_1(N_M + 1) + \psi_1(N_M - k + 1) \end{aligned} \quad (20)$$

C. HUWE Approximation

To determine exactly the relevant moments of Y_k , the integrals (21) should be performed.

$$\begin{aligned} \mu_{Y_k} &= \int_0^1 \ln(-\ln(1-f)) \frac{f^{k-1}(1-f)^{N_M-k}}{\text{Beta}(k, N_M-k+1)} df \\ \sigma_{Y_k}^2 &= \int_0^1 (\ln(-\ln(1-f)) - \mu_{Y_k})^2 \frac{f^{k-1}(1-f)^{N_M-k}}{\text{Beta}(k, N_M-k+1)} df \end{aligned} \quad (21)$$

Unfortunately, (21) cannot be solved in closed form, so HUWE uses an alternate method to approximate the moments of Y_k through the moments of Φ_k . Basically, the HUWE approximation is the assumption of the s -normality of Y_k .

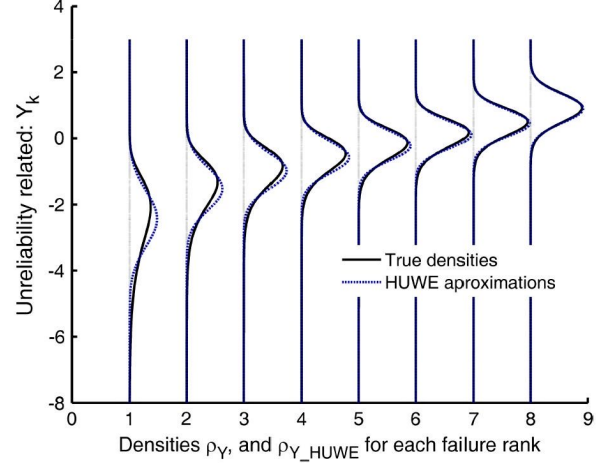


Fig. 3. True and HUWE approximated Y_k densities evolution along failure rank (for $N_M = 8$).

This assumption is domain coherent because the domain of a s -normal distribution is the whole real line $(-\infty, \infty)$, which matches the domain of Y_k because the successive application of transformations (2) and (3) maps the probability domain $F_k \in (0, 1)$ to $Y_k \in (-\infty, \infty)$. A deductive consequence of the s -normality of Y_k is that Φ_k should be assumed to be log-normally distributed because both are related by (3). Of course, the domain of Φ_k is the transform of $F_k \in (0, 1)$ by (2); that is, $\Phi_k \in (0, \infty)$, as should be expected for a genuine log-normal. The accuracy of HUWE will be discussed in more detail in Section II-D.

D. Y_k Moments Determination

By applying well known relations (22) between the first moments (μ_N , and σ_N^2) of a s -normal random variable N , and the first moments (μ_L , and σ_L^2) of the log-normal distributed variable $L = e^N$,

$$\begin{aligned} \mu_N &= \ln(\mu_L) - \frac{1}{2} \ln \left(1 + \frac{\sigma_L^2}{\mu_L^2} \right) \\ \sigma_N^2 &= \ln \left(1 + \frac{\sigma_L^2}{\mu_L^2} \right) \end{aligned} \quad (22)$$

to $\Phi = e^Y$, we can express the HUWE approximation as

$$\begin{aligned} \mu_{Y_k} &\approx \ln(\mu_{\Phi_k}) - \frac{1}{2} \ln \left(1 + \frac{\sigma_{\Phi_k}^2}{\mu_{\Phi_k}^2} \right) \\ \sigma_{Y_k}^2 &\approx \ln \left(1 + \frac{\sigma_{\Phi_k}^2}{\mu_{\Phi_k}^2} \right) \end{aligned} \quad (23)$$

Hence, (23) is more accurate as Y_k gets closer to s -normality.

To qualitatively show the accuracy of the HUWE approximation, Fig. 3 depicts the true, and approximate Y_k densities. It can be seen that HUWE provides a good approximation, even for low values of N_M and k , and that the approximation gets better when k grows.

A more precise analysis of the error introduced by HUWE approximation can be performed by estimating the Kullback-Leiber distance [28] from the true to the approximate density

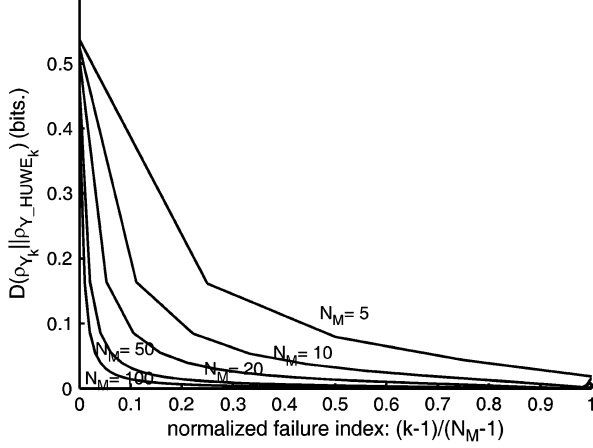


Fig. 4. Kullback-Lleiber information leakage caused by the approximation: $Y_k \approx Y_{HUWE_k}$.

(24). The Kullbak-Lleiber distance is a measure of the information leakage derived by assuming the approximated density $\rho_{Y_{HUWE}}$ instead of the true ρ_Y .

$$D(Y||Y_{HUWE}) = \int_{-\infty}^{\infty} \rho_Y(y) \log_2 \left(\frac{\rho_Y(y)}{\rho_{Y_{HUWE}}(y)} \right) dy \quad (24)$$

Eqn. (24) has been evaluated as a function of the normalized failure index $k-1/N_M-1$ for several values of N_M , and plotted in Fig. 4. The information leakage remains under 0.6 bits, and gets very small as k grows, especially for high values of N_M .

E. Weibull Parameter Estimation

Once μ_{Y_k} and $w_k = 1/\sigma_{Y_k}^2$ have been determined by (23), they are supplied to a WLS [22] regression algorithm as centralization and weight values for the response variable. The explanatory values X_k for the regression are derived directly as $X_k = \ln(t_k)$.

The moments of Y_k do not depend on $\{t_k\}$, but only on N_M and k , so they can be pre-computed before the experiment is done in order to improve time in repeated trials.

Using WLS in step E means that HUWE assumes that the data are uncensored because WLS considers only errors in Y_k , whereas data censoring also entails errors in X_k due to the uncertainty of t_k . As it is clear from Fig. 1, step E is procedurally independent of the previous ones, so HUWE steps A to D can be used also for censored data. However, to address the whole problem, a protocol for modeling time uncertainties has to be defined, and the use of double axis heteroscedastic special regression techniques [29] is required.

III. EXAMPLE

To clarify the HUWE methodology, we present here a simple example. Suppose we have performed a simple experiment with five widgets $N_M = 5$, and we have obtained the failure times shown below.

From test life data in Table I, we put in Table II the relevant quantities for the estimation. We begin by putting failure times

TABLE I
EXAMPLE TIME SERIES

t_k	t_1	t_2	t_3	t_4	t_5
(days)	0.9545	1.0195	1.7962	3.1409	3.8189

TABLE II
EXAMPLE OF THE HUWE PROCESS

t_k	X_k	k	μ_{ϕ_k}	$\sigma_{\phi_k}^2$	μ_{Y_k}	$\sigma_{Y_k}^2$
0.9545	-0.0465	1	0.2	0.04	-1.956	0.6931
1.0195	0.0194	2	0.45	0.1025	-1.0033	0.4096
1.7962	0.5857	3	0.7833	0.2136	-0.3936	0.2987
3.1409	1.1445	4	1.2833	0.4636	0.1254	0.248
3.8189	1.34	5	2.2833	1.4636	0.7019	0.2474

in the first column, and associated ranks in the third column. The abscissa coordinates in the second column are set to $X_k = \ln t_k$. Then, we apply the HUWE methodology in Fig. 1. Step A states the unreliability model (12) for $N_M = 5$; that is, $F_k \sim \text{Beta}(k, 6 - k)$; step B gives (20) to obtain $\mu_{\Phi_k} = \psi_0(6) - \psi_0(6 - k)$, and $\sigma_{\Phi_k}^2 = -\psi_1(6) + \psi_1(6 - k)$ in the fourth, and fifth columns. Assuming HUWE approximation (step C), use (23) of step D to get μ_{Y_k} , and $\sigma_{Y_k}^2$ for the sixth, and seventh columns.

Finally, in step E, X_k , μ_{Y_k} and $\sigma_{Y_k}^2$ are supplied to WLS [22] to achieve the minimization of (8). This result yields the slope m , and the y-intercept b of the regression line as

$$m = \frac{-\left(\sum_{k=1}^{N_M} \frac{1}{\sigma_{Y_k}^2}\right) \left(\sum_{k=1}^{N_M} \frac{X_k \mu_{Y_k}}{\sigma_{Y_k}^2}\right) + \left(\sum_{k=1}^{N_M} \frac{X_k}{\sigma_{Y_k}^2}\right) \left(\sum_{k=1}^{N_M} \frac{\mu_{Y_k}}{\sigma_{Y_k}^2}\right)}{\left(\sum_{k=1}^{N_M} \frac{X_k}{\sigma_{Y_k}^2}\right)^2 - \left(\sum_{k=1}^{N_M} \frac{1}{\sigma_{Y_k}^2}\right) \left(\sum_{k=1}^{N_M} \frac{X_k^2}{\sigma_{Y_k}^2}\right)} \quad (25)$$

$$b = \frac{\left(\sum_{k=1}^{N_M} \frac{X_k}{\sigma_{Y_k}^2}\right) \left(\sum_{k=1}^{N_M} \frac{X_k \mu_{Y_k}}{\sigma_{Y_k}^2}\right) + \left(\sum_{k=1}^{N_M} \frac{X_k^2}{\sigma_{Y_k}^2}\right) \left(\sum_{k=1}^{N_M} \frac{\mu_{Y_k}}{\sigma_{Y_k}^2}\right)}{\left(\sum_{k=1}^{N_M} \frac{X_k}{\sigma_{Y_k}^2}\right)^2 - \left(\sum_{k=1}^{N_M} \frac{1}{\sigma_{Y_k}^2}\right) \left(\sum_{k=1}^{N_M} \frac{X_k^2}{\sigma_{Y_k}^2}\right)} \quad (26)$$

Using (25) and (26) for the data in Table II, and $N_M = 5$ gives $m = 1.440$, and $b = -1.338$. Thus, according to (4), the estimates $\hat{\beta}_{HUWE} = m = 1.440$, and $\hat{\eta}_{HUWE} = e^{-(b/m)} = 2.53$ days are obtained

IV. EVALUATION PROCEDURE

In this section, we will describe the procedure, depicted in Fig. 5, that is used to evaluate HUWE. The HUWE performance will be determined by contrasting its ability to guess the (hidden) value of the Weibull parameters $\{\eta_{true}, \beta_{true}\}$ from a succession of failure times, against the ability of other methods to do the same as references. The successions of failure times that are supplied to the competing methods are synthesized as

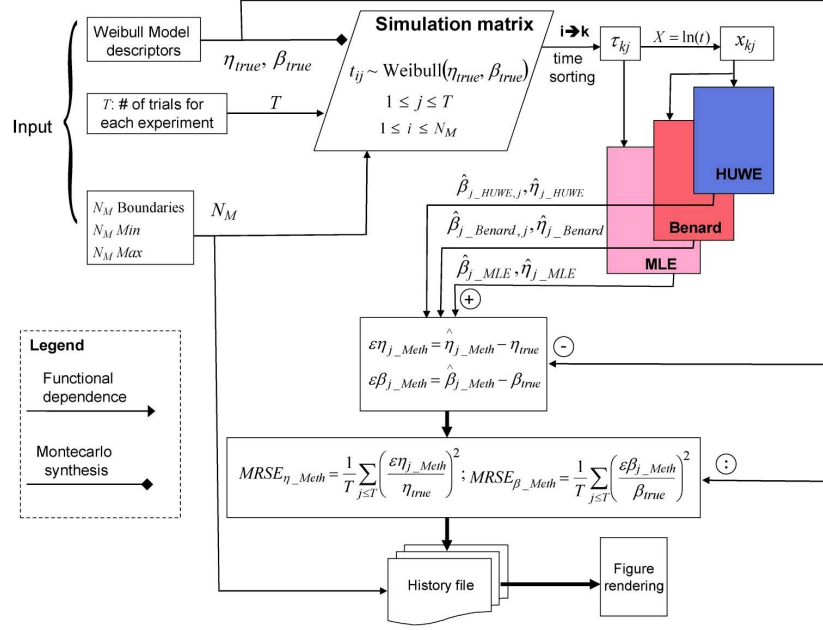


Fig. 5. Monte Carlo test procedure explanation.

complete, and s -independent $Weibull(\eta_{true}, \beta_{true})$ pseudo-random samples. Each succession defines a trial (that is indexed as j), and a large number of trials T are generated to accurately evaluate the features of the methods.

The methods used as references are Benard's, and MLE. More specifically, and in the context of the evaluation, we describe the methods.

- Benard's method uses (6) to obtain F_k , then determines Y_k and X_k by (5), and eventually achieves Weibull parameters by ordinary least squares minimization of the residual (7).
- MLE is solved by applying the iterative algorithm described in the classical article [4].

Once the parameter estimations $\hat{\eta}_{j_Meth}, \hat{\beta}_{j_Meth}$ offered by each competing method for the j -th trial have been obtained, the errors $(\varepsilon\eta_{j_Meth}, \varepsilon\beta_{j_Meth})$ of each are given by

$$\begin{aligned} \varepsilon\eta_{j_Meth} &= \hat{\eta}_{j_Meth} - \eta_{true} \\ \varepsilon\beta_{j_Meth} &= \hat{\beta}_{j_Meth} - \beta_{true} \end{aligned} \quad (27)$$

Above, the sub-index $Meth$ (Method), is a dummy that stands for any particular method name (for instance, to specify the MLE method, $\varepsilon\eta_{j_Meth}$ becomes $\varepsilon\eta_{j_MLE}$).

Examining Fig. 5 in more detail, at the beginning of the evaluation process, the values of the Weibull target parameters $(\eta_{true}, \beta_{true})$ are settled, together with the desired range of test life sizes (number of widgets) one wants to investigate $[N_M Max, N_M Min]$, and the number of trials T , the number of Monte Carlo independent repetitions of each test life. Then the program expands the N_M range in logarithm equally-spaced values, and for each one it generates a stochastic $N_M \times T$ sized matrix t_{ij} of s -independent Weibull failure times. Once t_{ij} has been generated, its columns are ordered giving rise to another matrix τ_{kj} such that the j -th column of τ_{kj} will contain the rank-indexed times of failures for the j -th trial. The data in

τ_{kj} are then supplied to the three estimation methods under investigation to obtain the estimations $\hat{\eta}_{j_Meth}, \hat{\beta}_{j_Meth}$, and the errors $(\varepsilon\eta_{j_Meth}, \varepsilon\beta_{j_Meth})$ mentioned above.

To quantify the ability of a method to hit the target values $\beta_{true}, \eta_{true}$, we define the Mean Relative Square Error ($MRSE$) measures from the error series $\varepsilon\eta_{j_Meth}, \varepsilon\beta_{j_Meth}$ as

$$MRSE_{\eta_Meth} = \frac{1}{T} \sum_{j=1}^T \left(\frac{\varepsilon\eta_{j_Meth}}{\eta_{true}} \right)^2 \quad (28)$$

$$MRSE_{\beta_Meth} = \frac{1}{T} \sum_{j=1}^T \left(\frac{\varepsilon\beta_{j_Meth}}{\beta_{true}} \right)^2 \quad (29)$$

where the sums in (28) and (29) are over all the T Monte Carlo trials.

Mean Square Error (MSE), often used as a quality measure of estimators, can be obtained in a direct way from $MRSE$ by means of

$$\begin{aligned} MSE_{\eta_Meth} &= \eta_{true}^2 MRSE_{\eta_Meth} \\ MSE_{\beta_Meth} &= \beta_{true}^2 MRSE_{\beta_Meth} \end{aligned} \quad (30)$$

$MRSE$ are preferable to MSE when we want to compare performances over a wide range of target values of parameters $\eta_{true}, \beta_{true}$, because $MRSE$ are much more stable against changes of such values than MSE . In fact, due to scale considerations [11] on the Weibull law (1), $MRSE_{\eta_Meth}$ and $MRSE_{\beta_Meth}$ do not depend on η_{true} at all. On the other hand, $MRSE_{\beta_Meth}$ also appears to be functionally independent of β_{true} as it will be accounted for in the evaluation results of the next section (see Fig. 6). This double independence lets us summarize all the information about the β estimators in a single graph.

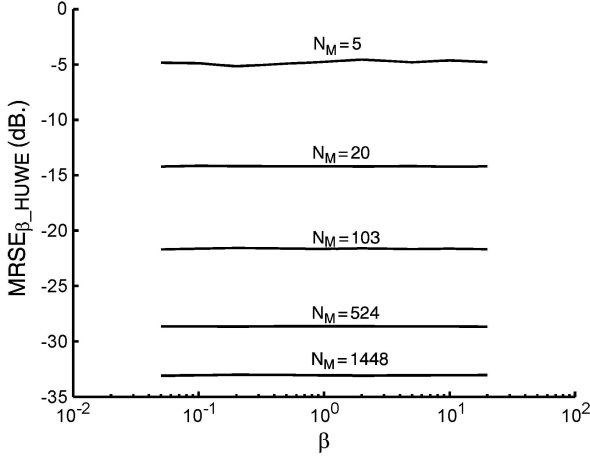


Fig. 6. $MRSE_\beta$ independence from β_{true} value.

Both $MRSE_\eta$, and $MRSE_\beta$ are dimensionless quadratic measures, so they can be expressed in a natural way in logarithmic units (31).

$$\begin{aligned} MRSE_\eta(dB.) &= 10 \log_{10}(MRSE_\eta) \\ MRSE_\beta(dB.) &= 10 \log_{10}(MRSE_\beta) \end{aligned} \quad (31)$$

Once $MRSE$ qualifiers have been obtained for the desired test life sizes, parameters values, and methods of interest, they are stored in files, and post-processed to render figures.

V. RESULTS

In this section, we will show the results of applying the methodology described above to the evaluation of the three methods that are going to be compared.

To obtain $MRSE$, we have established the following environment.

- A number of trials $T = 40000$ have been synthesized.
- A range of 36 log-spaced values for N_M have been selected between $N_{MMin} = 4$, and $N_{MMax} = 4000$.
- As η is a scale parameter, changing its value simply affects the failure times by a multiplicative constant factor [11], so it is enough to perform the evaluations for $\eta_{true} = 1$.
- β_{true} values have been selected from the range $0.05 < \beta_{true} < 20$.

A. Shape Parameter (β) Estimation

We can observe in Fig. 6 that $MRSE_\beta$ remains almost unchanged against changes of the β_{true} target values.² This is a good feature of $MRSE_\beta$ as a quality measure of β estimations, and allows us to reduce the analysis to the case where $\beta_{true} = 1$. Thus, Fig. 7 shows $MRSE_\beta(dB.)$ for each method, and $\beta = 1$.

Fig. 7 shows the quality of β estimators, $MRSE_\beta$ as a function of N_M . Here, $MRSE_\beta$ are very widespread due to their strong (functional) dependence with N_M , thus blurring the contrast between the three methods. So to get a graph that highlight better the differences, it is very useful to establish a reference $MRSE_{\beta_Analytic} \approx MRSE_{\beta_Meth}$ competent to model the

²For the sake of clarity, Fig. 6 only shows $MRSE_{\beta_HUWE}$, results for other methods lead to the same conclusion.

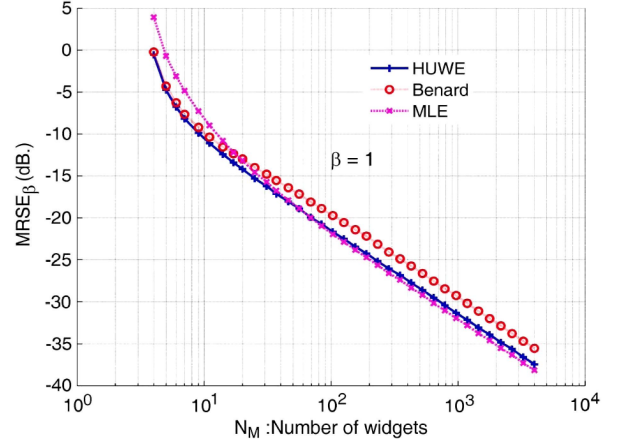


Fig. 7. Compared studio of $MRSE_\beta$ as a function of N_M .

common dependence of the behavior of the methods with N_M . Reasonable requirements for $MRSE_{\beta_Analytic}$ are that

- it should follow as closely as possible the global behavior of the methods, especially in the asymptotic limits;
- it should be easily computable, without the need of Monte Carlo synthesis resources; and
- it should not contain large or difficult to manage constants.

A heuristic choice for $MRSE_{\beta_Analytic}$ that meets well these requirements is

$$MRSE_{\beta_Analytic} = \frac{1}{(N_M - 3.4)}. \quad (32)$$

By writing (32) in logarithmic units, we have

$$MRSE_{\beta_Analytic}(dB.) = -10 \log_{10}(N_M - 3.4). \quad (33)$$

By using $MRSE_{\beta_Analytic}(dB.)$ as a reference, we can define the accuracy gain figures $GAIN_{\beta_Meth}$ for each method (34). Of course, unlike $MRSE$, accuracy gains are defined in such a way that are larger as methods perform better.

$$GAIN_{\beta_Meth}(dB.) = MRSE_{\beta_Analytic}(dB.) - MRSE_{\beta_Meth}(dB.) \quad (34)$$

Under these conventions, $GAIN_\beta$ have been represented in Fig. 8 for $\beta_{true} = 1$. Results for other values of β_{true} follow the same behavior.

B. Scale Parameter (η) Estimation

To define accuracy gain figures for η estimators, a global reference behavior $MRSE_{\eta_Analytic}$ has been also defined for them. But unlike $MRSE_{\beta_Analytic}$, $MRSE_{\eta_Analytic}$ depends on β_{true} in a somewhat complex way. A good heuristic fit for $MRSE_\eta$ has been found to be (35).

$$MRSE_{\eta_Analytic} = \frac{\text{Exp}\left(\beta_{true}^{\frac{5}{3}} N_M^{\frac{3}{4}}\right)}{\beta_{true}^2 (N_M - 2)} \quad (35)$$

By writing (35) in logarithmic units, we have

$$MRSE_{\eta_Analytic}(dB.) = -10 \log_{10}(N_M - 2) - 20 \log_{10} \beta_{true} + \frac{10 \log_{10} e}{\beta_{true}^{\frac{5}{3}} N_M^{\frac{3}{4}}}. \quad (36)$$

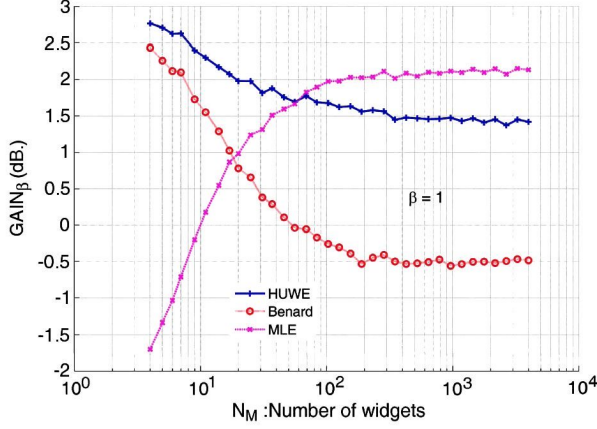


Fig. 8. β accuracy gains with respect to $MRSE_{\beta-Analytic}$ as a function of N_M .

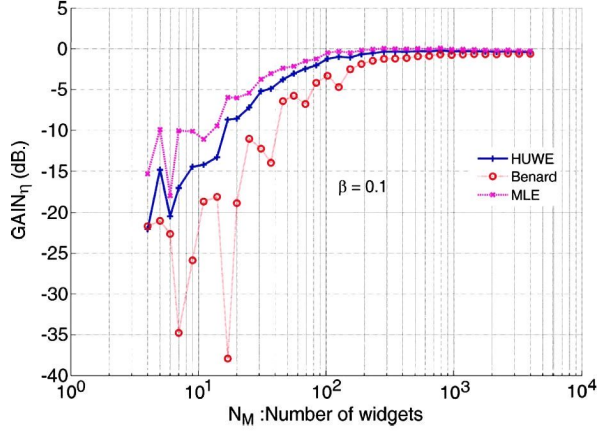


Fig. 9. η accuracy gains with respect to $MRSE_{\eta-Analytic}$ as a function of N_M for $\beta_{true} = 0.1$.

By using $MRSE_{\eta-Analytic}(dB.)$ as reference, we can define gain figures for each method.

$$GAIN_{\eta-Method}(dB.) = MRSE_{\eta-Analytic}(dB.) - MRSE_{\eta-Method}(dB.) \quad (37)$$

Under these conventions, in Figs. 9–11, accuracy gains with respect to the reference (36) have been represented for $\beta_{true} = 0.1$, $\beta_{true} = 1$, and $\beta_{true} = 20$, respectively.

C. Result Summary

With respect to β estimation, we can conclude from Fig. 8 that

- HUWE performs the best for low values of the number of widgets ($N_M < 65$);
- for very low values of the number of widgets $N_M < 20$, MLE performs the worst; and
- as $N_M \rightarrow \infty$, HUWE tends to perform better (2.0 dB.) than Benard's, and slightly worse (0.6 dB.) than MLE.

With respect to η estimation, we can conclude from Figs. 9–11 that

- the accuracy levels of the three methods are quite similar, disregarding the fact that when β_{true} , and N_M are both

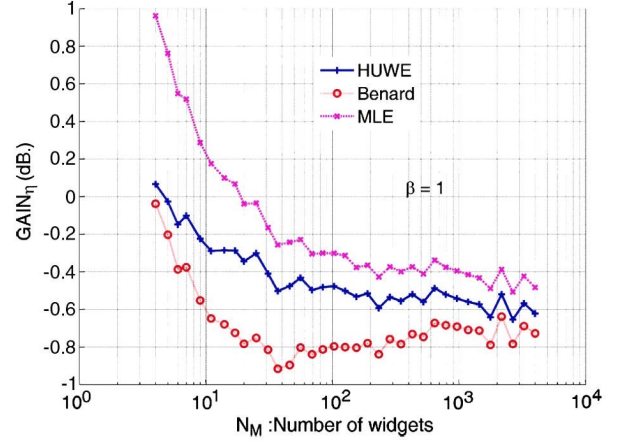


Fig. 10. η accuracy gains with respect to $MRSE_{\eta-Analytic}$ as a function of N_M for $\beta_{true} = 1$.

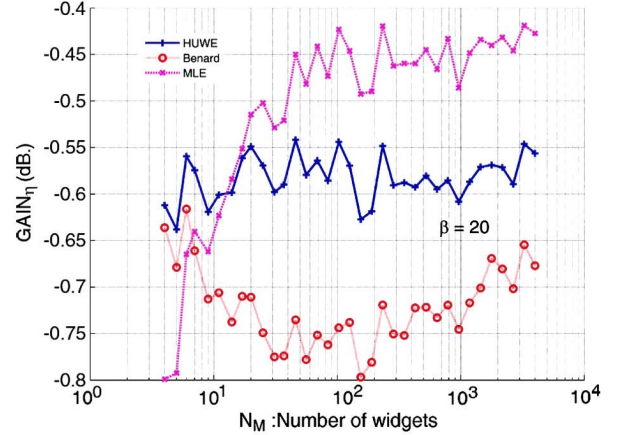


Fig. 11. η accuracy gains with respect to $MRSE_{\eta-Analytic}$ as a function of N_M for $\beta_{true} = 20$.

small, Benard's method does much worse than the others; and

- when $N_M \rightarrow \infty$, regardless of the β_{true} value, a small difference of about 0.15dB. remains, where the best is MLE, then HUWE, and then Benard's method.

Note that the advantage of HUWE against Benard's method can have economic significance as it offers an important reduction in the required number of widgets $-\Delta N_M/N_M$. For example, regarding β estimation, this reduction can be obtained from Fig. 7, or can be estimated roughly for large values of N_M (38) by taking into account (32).

$$\lim_{N_M \rightarrow \infty} \frac{-\Delta N_M}{N_M} \approx 1 - 10^{-\frac{2D_b}{10}} = 37\% \quad (38)$$

Aside from the accuracy results, MLE has been found to be much more time consuming than other methods, especially for high values of N_M , even though HUWE pre-computation (see Section II-E) has not been used in the evaluation. Also, when the β_{true} value is far from $\beta_{true} = 1$, the MLE computational demand reaches the limits of the numerical representation (64 bit double-precision IEEE 754 [30]) used in the simulation, in such a way that numerical crashes occurred for $\beta_{true} < .02$;

and we experienced a lack of convergence, and infinite loops for $\beta_{true} > 10$.

VI. CONCLUSION

We presented HUWE, an algorithm for estimating Weibull parameters from life tests that offers a good trade-off alternative to the traditional Weibull estimators.

HUWE is based on an approximation, the assumption of s -normality for the data unreliability related variables Y_k . This approximation allows us to express analytically the first two moments of Y_k in a nice symmetrical form. Having determined the means and variances of Y_k , the Weibull parameters η and β are estimated by fitting the data to a linear model using WLS.

HUWE has been Monte Carlo evaluated against Benard's approximation, and MLE. The evaluation results are as follows.

- HUWE is more robust, and computationally more efficient than MLE. Though in some cases the accuracy of HUWE is slightly lower than that of MLE, the global performance of HUWE is better when one considers the whole range of working cases.
- HUWE significantly improves the performance of Benard's approximation. For large enough numbers of widgets, say $N_M > \sim 60$, HUWE is able to get similar confidence levels for the estimators of Weibull parameters than Benard's, but using 37% less widgets.

In short, HUWE is a robust, accurate, flexible algorithm that has global advantages against traditional Weibull estimators, constituting an appealing choice to be embedded in automated test life systems.

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